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Exposure Monitoring Strategies for Applying Low-Cost PM Sensors to Assess Flour Dust in Industrial Bakeries

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Abstract

Low-cost particulate matter (PM) sensors provide new methods for monitoring occupational exposure to hazardous substances, such as flour dust. These devices have many possible benefits, but much remains unknown about their performance for different exposure monitoring strategies in the workplace. We explored the performance of PM sensors for four different monitoring strategies (time-weighted average and high time resolution, each quantitative and semi-quantitative) for assessing occupational exposure using low-cost PM sensors in a field study in the industrial bakery sector. Measurements were collected using four types of sensor (PATS+, Isensit, Airbeam2, and Munisense) and two reference devices (respirable gravimetric samplers and an established time-resolved device) at two large-scale bakeries, spread over 11 participants and 6 measurement days. Average PM2.5 concentrations of the low-cost sensors were compared with gravimetric respirable concentrations for 8-h shift periods and 1-min PM2.5 concentrations of the low-cost sensors were compared with time-resolved PM2.5 data from the reference device (quantitative monitoring strategy). Low-cost sensors were also ranked in terms of exposure for 8-h shifts and for 15-min periods with a shift (semi-quantitative monitoring strategy). Environmental factors and methodological variables, which can affect sensor performance, were investigated. Semi-quantitative monitoring strategies only showed more accurate results compared with quantitative strategies when these were based on shift-average exposures. The main factors that influenced sensor performance were the type of placement (positioning the devices stationary versus personal) and the company or workstation where measurements were collected. Together, these findings provide an overview of common strengths and drawbacks of low-cost sensors and different ways these can be applied in the workplace. This can be used as a starting point for further investigations and the development of guidance documents and data analysis methods.

Keywords: bakery; exposure; flour dust; low-cost devices; monitors; occupational; particulate matter (PM); sensors

What's Important About This Paper?

Low-cost particulate matter (PM) sensors have been used increasingly in workplace settings, but there remain questions about their performance and utility for different exposure monitoring strategies. This study found that sensors performed better at ranking shift-average exposures than quantifying those exposures relative to reference instruments, and that performance was more robust for stationary than personal sampling. New monitoring strategies can be developed to optimize the value of exposure data obtained from PM sensors.

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Introduction

Exposure to hazardous substances in the workplace is estimated to account for 1.2 million deaths worldwide per year, which is four times more than deaths due to work-related injuries (Driscoll *et al.*, 2020). Additionally, occupational exposures may result in nonmalignant diseases which persist throughout a person's life (Driscoll *et al.*, 2020). Studies estimated that up to 30% of the incidence of various respiratory diseases are related to exposure to hazardous substances in the workplace (Blanc *et al.*, 2019). Therefore, prevention of occupational exposures is an important aspect in improving general health and decreasing financial burdens on society.

One example of occupational exposure can be found in industrial bakeries. Flour dust contains multiple allergens and prolonged exposure can result in adverse health effects, such as conjunctivitis and bakers asthma (Stobnicka and Górny, 2015). Occupational exposure to flour dust remains a prevalent problem, with high levels of exposure still found in some bakeries (Kirkeleit *et al.*, 2017; Martinelli *et al.*, 2020). Flour dust is a highly dynamic exposure with significant variations in time and space. One study reported that over 75% of the cumulative exposure originated from short events of high exposure (Meijster *et al.*, 2008). Moreover, exposure levels may vary significantly between tasks and prevention require targeted control strategies (Baatjies *et al.*, 2014; Martinelli *et al.*, 2020). This makes adequate monitoring of exposure situations crucial toward appropriately applying risk minimizing measures and prevention of occupational diseases.

Low-cost optical particulate matter (PM) sensors have the potential for a major contribution toward occupational hygiene (American Industrial Hygiene Association, 2016; Committee on Incorporating 21st Century Science into Risk-Based Evaluations, 2017; Morawska et al., 2018; Goede *et al.*, 2020; Howard *et al.*, 2022). Monitoring the occupational exposure to hazardous substances can become more continuous, automated, and remotely controlled thanks to the availability of devices at lower cost, of smaller size, and with the possible real-time feedback to the users. The accuracy of low-cost PM sensors has been reported in multiple laboratory and field applications and is generally lower compared with traditional measurement equipment (Jones *et al.*, 2016; Lewis and Edwards, 2016; Kelly *et al.*, 2017).

While measurement accuracy is of importance, the added value of low-cost sensors may not solely depend on it. Less accurate measurements, but at higher spatial and temporal resolution, could contribute to monitoring and preventing high exposures by expanding the view on how these sensors could be applied in the workplace and which type of information could be generated. For instance, new continuous monitoring systems could be developed or sensors could be used as a more accessible first investigation method in a tiered exposure control approach. Data could be used in combination with existing exposure models or for the communicating exposure levels over time or space (Zuidema et al., 2019a; Goede *et al.*, 2020). In this way, low-cost sensors may be applied for different exposure monitoring strategies aimed at prevention and supplement existing validated methods, rather than replacing them (Howard *et al.*, 2022). The performance of applying low-cost sensors for different monitoring strategies remains poorly studied.

The aim of this study is to explore the use of low-cost PM sensors for different exposure monitoring strategies in the industrial bakery sector. A field study was performed at two industrial bakeries, collecting exposure measurements using four types of low-cost sensors and two types of traditional measurement equipment. Four different monitoring strategies were investigated: (i) estimating the average exposure over a full working shift, (ii) ranking shifts based on the relative average exposures within a group of shifts, (iii) measuring exposure levels with high temporal resolution, and (iv) ranking exposure during short time periods within a single shift. The performance of the sensors for each monitoring strategy was determined by comparing the results with the reference measurements. When possible, we also investigated which factors may have affected the performance. These factors include whether the sensors were worn personally or stationary and if responses differed between the bakeries or between workstations within the bakeries, as well as differences in some methodological choices, such as averaging period length.

Methods

Study design

The study was performed at two industrial bakeries in the Netherlands. Measurements were taken over 3 days per company between 7 and 28 November 2019. This relatively short measurement period was chosen not to overburden the volunteers. The first bakery (bakery 1) was a large-scale artisan bakery where more manual tasks were performed. The production area was approximately 1000 m^2. Main control measures included local exhaust ventilation during manual dispensing of powders and unextracted enclosures for mechanical dispensing and kneading of dough. Cleaning was performed under wet conditions in the production area and dry conditions near the oven with occasional use of compressed air. The second bakery (bakery 2) was a more industrialized bread bakery where automated tasks were more prevalent, and with employees assigned to specific workstations or operations. The production area was approximately 5000 m². Risk management measures were similar to the first bakery with the addition of a general ventilation system. Cleaning was performed both wet and dry with occasional use of compressed air. In both bakeries, no personal respiratory protective equipment was used.

In both bakeries, employees worked at one workstation within the bakery for a whole shift, so this workstation was used as the main contextual information in the study. Which employee worked at which workstation was registered manually by the field workers. In bakery 1, this was mainly related with a specific task that was performed (weighing, doughmaking, production and use of oven), while workstations at bakery 2 were complete production lines that the employees operated (lines A, B, and C). Workstations were generally about 50 m² in size. No measurements were collected after the dough was baked, since no flour was used during cooling and packaging processes and flour dust exposure was assumed to be minimal at that point.

Measurements were collected for 8-h shifts with up to five workers and two measurement stations per day per bakery. An overview of the work schedule is given in Supplementary Table S1 (available at *Annals of Work Exposures and Health* online).

Measurement devices

Technical specifications of all measurement devices and the number of used devices are given in Table 1.

Low-cost PM sensors

Four models of PM sensors were used. The PATS+ (Berkeley air, CA, USA) and Isensit (Plantower PMS5003 sensor, VTEC, Eindhoven, the Netherlands) sensor were used both for personal and stationary monitoring. The Munisense AQ1 (Alphasense OPC-R1 sensor, Munisense, Leiden, the Netherlands) and AirBeam2 (Plantower PMS7003 sensor, Habitatmap, Brooklyn, NY, USA) were used only for stationary monitoring. For the current study, only PM2.5 measurements were used for analysis. Sensor selection for the study was based on performance and accuracy during previous laboratory testing (Ruiter *et al.*, 2020), commercial availability and input from the authors. This resulted in a selection of sensors with different sensing principles (optical particle counters or photometers) to provide a appropriate reflection of currently available PM sensors. The selection procedure led to some overlap in the sensing units used in the sensors (for the Airbeam2 and Isensit sensors). It should be noted that all PM sensors (except the PATS+) were developed for environmental settings. Still, these sensors may have a use for occupational purposes and were therefore included in the study. The Airbeam2 and

Table 1. Specifications of the measuring equipment used in this study.

PM sensors and reference equipment	Type	PM size fractions	Data storage	Dimensions (cm)	Weight (g)	Additional sensors	Measuring frequency	*N* personal	*N* stationary
PATS+ (Sharp GP2Y1014)	Low-cost sensors	PM2.5	Internal	13 × 7.2 × 3.3	110	Temperature, humidity	60 s	5	1
Isensit (Plantower PMS5003)	Low-cost sensors	PM1, PM2.5, and PM10	Bluetooth (gateway)	5 × 3 × 7	80	Temperature, humidity	60 s	5	2
Munisense AQ1 (Alphasense OPC-R1)	Low-cost sensors	PM2.5	Wifi	17 × 10 × 10	320	Temperature, humidity	~1 s		5
AirBeam2 (Plantower PMS7003)	Low-cost sensors	PM1, PM2.5, and PM10	Wifi or Bluetooth (phone app)	10 × 3 × 15	140	Temperature, humidity	60 s		3
Cyclone sampler 225-69 + GilAir personal air pump	Reference	Respirable	N/A	7 × 7 × 8 + 11 × 6 × 6	50 + 580		N/A	5	3
APS 3321	Reference	0.5–20 µm over 52 channels	Connected computer	18 × 30 × 38	10 000		15 s		1

The left column provides the name of the sensor model with, if known, the sensing element in brackets; *N* is the number of devices that were used for personal and/or stationary measurements.

Munisense were not used as wearable devices not to overburden the participants.

Gravimetric respirable dust

Respirable dust was measured in the breathing zone of the workers and at stationary positions using 225-69 cyclone samplers (SKC Ltd, Dorset, UK), carbon fiber (CF) filters and GilAir air pumps (Sensidyne, St. Petersburg, FL, USA) at 3 l min^{-1}. The filters were conditioned and weighed in a controlled room with a temperature of 20°C and relative humidity of 50% and were weighed alongside blank filters after neutralization of charges using a MX5 microbalance (Mettler Toledo, Tiel, The Netherlands). Respirable measurements were carried out as they are more directly comparable to the PM2.5 fraction that is measured by the PM sensors. Filters were analyzed gravimetrically based on NIOSH method 0600 (NIOSH, 1998). The limit of detection (LOD) for gravimetrical analysis was calculated as three times the average standard deviation of triplicate blank filters (Health and Safety Executive, 2014). The LOD was 2.58 µg, which translates to a concentration of 1.79 µg m^{-3} for 8 h of sampling.

High-resolution monitor

An aerodynamic particle sizer (APS) 3321 was used as a high-resolution reference measurement. The measurement frequency was set to 15 s. Mass concentrations for the APS were calculated according to the manufacturers' instructions based on the bin size, shape, and density of the particles. The density was set to 0.8 g cm^{-3} and the dynamic shape factor was set to 1.75, which was assumed to represent the amorphous shape of flour dust (Laurière *et al.*, 2008). The PM2.5 fraction was calculated as the sum of the mass concentrations of the APS size bins smaller than 2.5 µm, plus an interpolated concentration from the two bins spanning 2.5 µm.

Device positioning

Equipment was attached to the workers using a nylon harness, which included all personal measurement instruments so that comparisons were independent of worker behavior. Personal equipment was removed during breaks. Positioning of the personal sensors was randomized with one sensor on the left and one on the right side of the worker harness and on the upper half of the worker's chest near the breathing zone (Supplementary Fig. S1, available at *Annals of Work Exposures and Health* online). Equipment at stationary locations was set up on a tripod with the inlets of measuring equipment at 1.5 m from the ground in the area where the workers performed their main tasks (i.e. the workstation). The tripod was positioned preferably near or in between main pieces of equipment where exposure may occur such as kneaders or conveyor belts. Five measurement stations were set up per company. One Munisense sensor was placed at each station. Airbeam2 sensors and gravimetric samplers were deployed at three main stationary locations. One APS, one PATS+, and one Isensit were available for stationary measurements, and these were placed side-by-side at a different station each day. At bakery 1, no APS measurements were collected at the production workstation due to practical constraints. Any PM sensors that were not in use for personal measurements were placed at stationary locations.

Exposure monitoring strategies

Four different exposure monitoring strategies of low-cost sensors were investigated, depicted graphically in Fig. 1. The first monitoring strategy resembles common practice in occupational exposure assessment where exposures are measured using filters and air pumps for prolonged periods, providing average worker exposures. These averages are weighted for the time a worker is exposed and the resulting 8-h time-weighted average is compared against an occupational exposure limit (Kirkeleit *et al.*, 2017; Martinelli *et al.*, 2020). The second monitoring strategy that is investigated is a less quantitative alternative for using averaged exposure data, namely the ranking of 8-h shifts (i.e. ordering the measured shifts from lowest to highest exposed and considering the relative ranking of a shift, without focusing on quantified exposure concentrations). This can be used to find the relatively highest exposed workers or tasks at a company or to find the days with highest exposures during a measurement week, which may provide a useful basis for exposure management, without relying on the absolute accuracy of the low-cost sensor. The third monitoring strategy is making use of the high temporal resolution of the exposure measurements over time. Low-cost sensors generate exposure data points every couple of seconds or minutes and provide a profile of peak exposure throughout a shift. This information can be used to find when and where highest exposure occur, which is currently occasionally done using high- or medium-cost equipment (Meijster *et al.*, 2008). Due to their low cost, these PM sensors could be deployed more widely at more locations in the workplace. They can also be worn in the breathing zone by workers. The fourth monitoring strategy is to use the measurements for one shift and calculate average exposures for smaller time periods, for example 15 min, and ranking these 15-min averages within the shift. This gives an overview of during which 15-min periods exposure was highest, without relying on the absolute accuracy of the sensors. This ranking can give an indication of the periods where exposure was the highest, which can be used to give

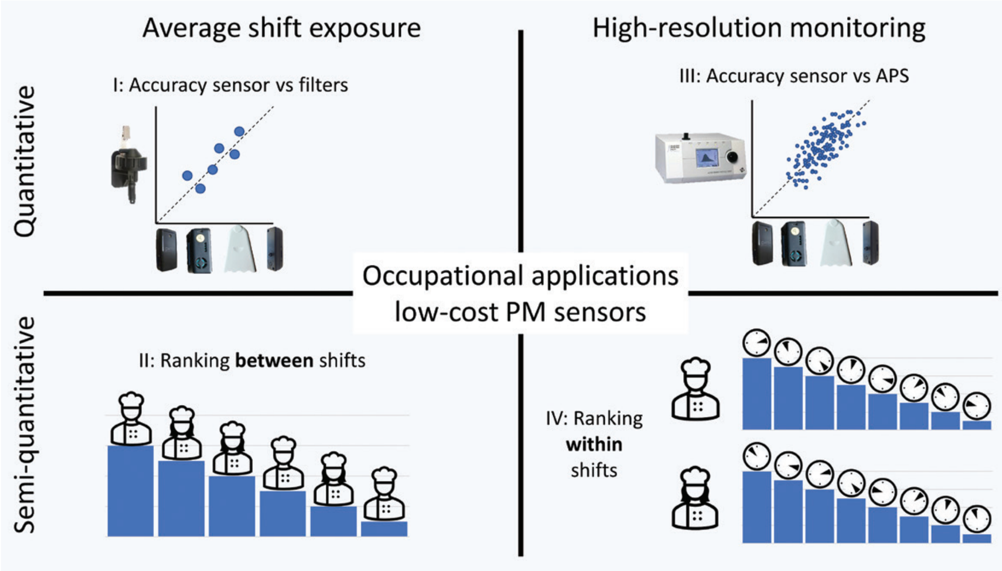

Figure 1. Schematic representation of the four sensor exposure monitoring strategies that were investigated in two bakeries.

a general starting point for identifying main exposure time and sources.

Statistical analysis

All analyses were performed in R version 3.5.1 (R Core Team, 2017). Sensor measurements below the LOD were substituted with half the LOD (5 µg m^{-3} for the PATS+ and 0.5 µg m^{-3} for all other devices). Sensor shift-average exposures were calculated as arithmetic means over the sampling period. High-resolution measurements were averaged to 1-min intervals. Data were normalized by log10 transformation to allow for linear regression analysis.

For the quantitative exposure monitoring strategies, linear regression analysis was used to calculate correlations (R^2) between averaged sensor measurements and gravimetric respirable dust or APS measurements (strategies I and III, respectively). These R^2 values were used to gain an indication of sensor performance for the monitoring strategy and to compare performance between sensors that were placed stationary or on a person. The influence on sensor performance of the company or workstation was investigated using mixed effect models (lme4 package in R, Bates *et al.*, 2015). Company or workstation effects were included in the model as random effects and the amount of variance explained by these effects was used to gain an indication of their effects on sensor performance. The linear regressions and mixed effect models were also depicted visually by scatter plots.

Spearman rank correlations were used to test sensor performance for the semi-quantitative exposure monitoring strategies. For monitoring strategy II, rankings of sensor shift averages were tested against rankings of the gravimetric for all shifts that were included in the study. Spearman estimates were used to compare the performance of the sensors. For monitoring strategy IV, when continuous real-time measurements were performed for 8 h (equivalent to a 8-h shift), 8-h measurement periods of the APS and sensors data were analyzed. For each 8-h shift, averages were calculated for 15-min periods, which were then ranked within the 8-h shift. Rankings of the sensors for each 8-h shift were compared against the ranking of the APS and Spearman estimates were used to compare the performance of the sensors. Periods of 15 min were chosen since this is the period generally used for short-term exposure limits.

Results

Data overview

A total of 11 bakers participated in the study, spread over 7 workstations in 2 bakeries. Gravimetric reference and sensor measurements during 8-h shifts were collected for 23 workers and 17 measurement stations. An overview of gravimetric reference measurements is given in Table 2. Respirable flour dust concentrations were comparable between the bakeries (ranges 2–274 and 4–197 µg m^{-3}). Exposure levels did differ within the bakeries. The highest mean exposures were found at the *production* and *Line C* workstations at bakeries 1 and 2, respectively. A total of 8893 APS high-resolution reference measurements were

Table 2. Overview of respirable gravimetric dust measurements. *N* describes the number of samples collected. The arithmetic mean, standard deviation (SD), extremes (min, max), and quartiles (p25, p50, and p75) are given. Values are in µg m⁻³.

Company	Workstation	*N*	Mean	SD	Min	p25	p50	p75	Max
Bakery 1	Doughmakery	4	24	18	5	15	22	31	48
Bakery 1	Oven	6	30	9	20	23	29	32	45
Bakery 1	Production	5	103	106	15	39	53	134	274
Bakery 1	Weighing	5	58	64	2	13	28	94	152
Bakery 2	Line A	9	30	22	4	13	33	41	74
Bakery 2	Line B	7	60	18	30	55	90	68	87
Bakery 2	Line C (off)	2	15	7	10				20
Bakery 2	Line C (on)	2	183	20	169				197

collected, which corresponds to 37.5 h of continuous measurements. An overview of all collected data is shown in Supplementary Fig. S2a and S2b (available at *Annals of Work Exposures and Health* online). No measurements were above the Dutch limit value for respirable dust of 5000 µg m^{-3}.

Exposure monitoring strategy I: estimation of shift-average exposure

Performance for estimating shift-average exposures differed mainly between stationary and personally placed sensors. Stationary sensors showed roughly comparable performance, with correlations ranging 0.39–0.63 (Fig. 2a). The APS was included in this analysis to compare sensors with research-grade equipment. The APS was the most accurate instrument for quantitative gravimetric measurements, as expected, with a correlation of 0.96. When used for personal monitoring, larger differences were present in sensor performance. No correlation was observed for the Isensit (R^2 of −0.03), while correlations for the PATS+ were comparable to stationary placed sensors (R^2 of 0.6).

To put these results in perspective of a practical monitoring study, we calculated the correlation between gravimetric samples taken on the first and second measurement days (Supplementary Fig. S3, available at *Annals of Work Exposures and Health* online) and compared these to the correlations between sensor and gravimetric samples taken on the same day (Fig. 2a). Substantial variation between the two measurement days was observed (R^2 = 0.19). Compared with the correlations that were observed between sensor and reference (R^2 of up to 0.63).

To further explore which factors may contribute to sensor inaccuracy, we explored differences between the two companies (Fig. 2b). Company effects were largest for the situations where the absolute levels of variance were also highest. The PATS+, when used in stationary position and the Isensit, when used in stationary position or as a personal device, had associated variance ranging from 0.16 to 0.57, with the company contributing to 40–79% of this variance. Variance for the other sensors ranged from 0.02 to 0.1 with the company contributing to 0–23% of this variance. The low amounts of base or unexplained variance indicate that the company effect is a main source of error. This means that when a sensor shows lower accuracy, this may be related to the company where sensors were used.

Sensors and APS exhibited some underestimation, shown as an upward deviation from the 1:1 line. Regression models were comparable for all stationary sensors, with intercepts between 0.67 and 0.86 and slopes between 0.61 and 0.77. When transformed to a nonlinear model, intercepts above 0 show a linear underestimation by the sensor and slopes below 1 indicate sensor responses exponentially decrease as concentrations increase. We investigated if the underestimation could be reduced by precalibrating the sensors using a calibration model developed in the laboratory (Ruiter *et al.*, 2020), by comparing the precalibrated bakery sensor data with those from the APS bakery data. However, the underestimation did not improve and as a consequence the laboratory precalibration model was not further used in this study (Supplementary Fig. S4, available at *Annals of Work Exposures and Health* online).

Exposure monitoring strategy II: ranking shift-average exposures

All types of sensor performed similar to each other for ranking 8-h shift-average exposures when placed stationary, with Spearman correlations between 0.73 and 0.82 (Fig. 3). The Isensit when worn as a personal device showed a low rank correlation of 0.08, while the PATS+ performance worn by workers was similar to when in stationary position (correlation

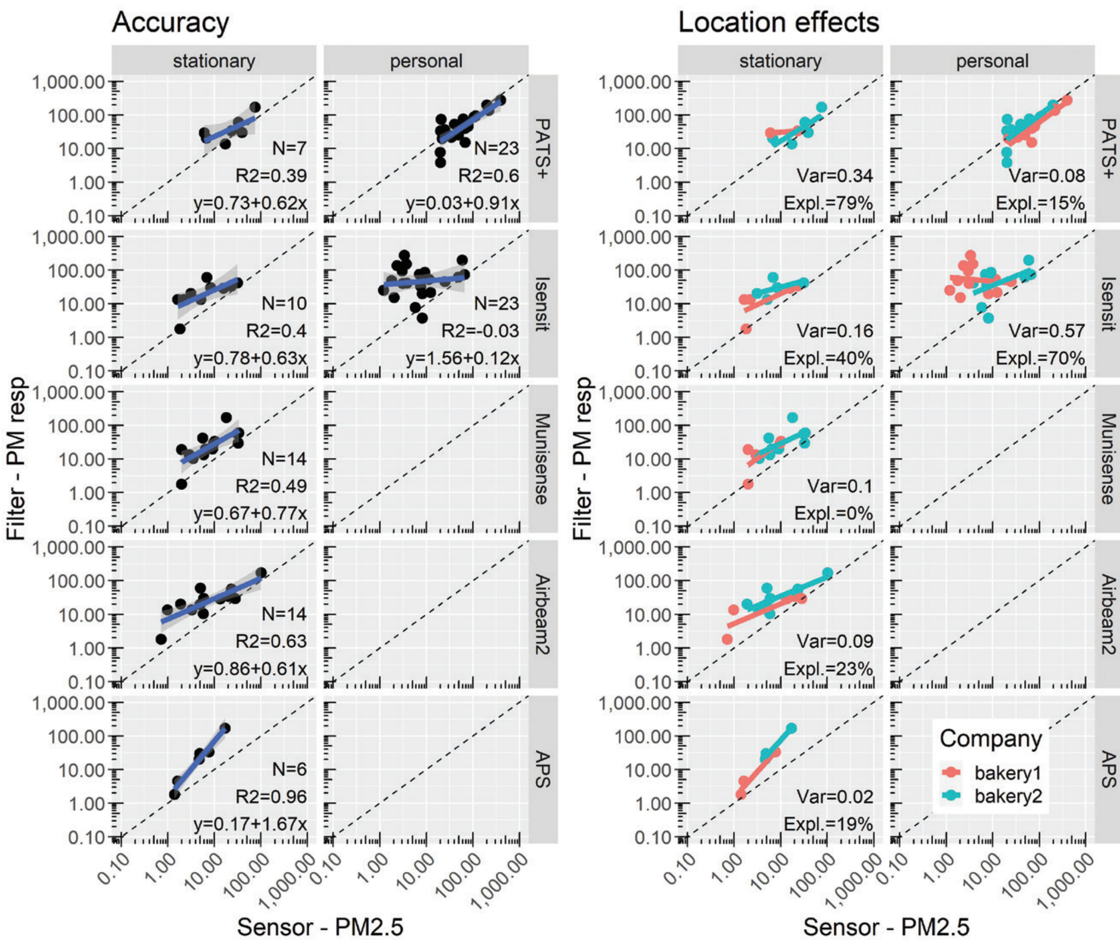

Figure 2. Sensor performance for estimating shift-average exposures. (a) Correlation between sensor and gravimetric samples and (b) effects of company. Var is the total amount of variance and Expl. is the percentage of variance explained by the company effect.

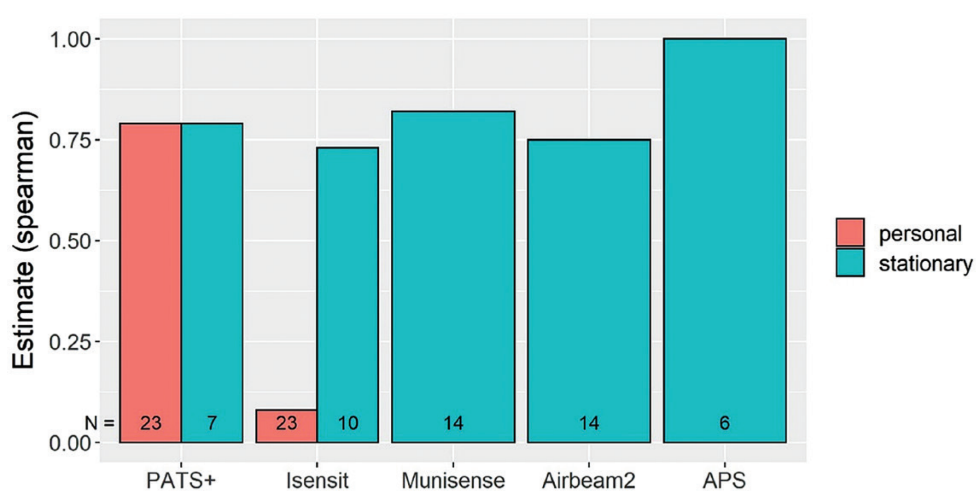

Figure 3. Rank correlations of 8-h average exposure measured by sensors compared with gravimetric samples.

of 0.79). The APS ranked all six shift-average measurements the same as the gravimetric measurements, giving a correlation of 1.00. These results are similar to the previous monitoring strategy, except that the performance between the sensors is more consistent and that the gap between each sensor type and the APS is smaller. This suggests that the overall performance for this monitoring strategy is greater and more robust (i.e. different sensor types give more similar results) compared with the first, quantitative monitoring strategy.

Exposure monitoring strategy III: high-resolution exposure monitoring

The performance for the time-resolved exposure monitoring strategy was comparable for most sensors (Fig. 4a). Correlation to the APS was slightly lower for the PATS+ (R^2 of 0.41) compared with the other sensors (R^2 ranging 0.58–0.65). The relatively lower performance of the PATS+ could be attributed to the large amount of measurements that were below the relatively high LOD of 10 μg m^{-3} (3698/5597 measurements or 66%). This LOD was set by the manufacturer

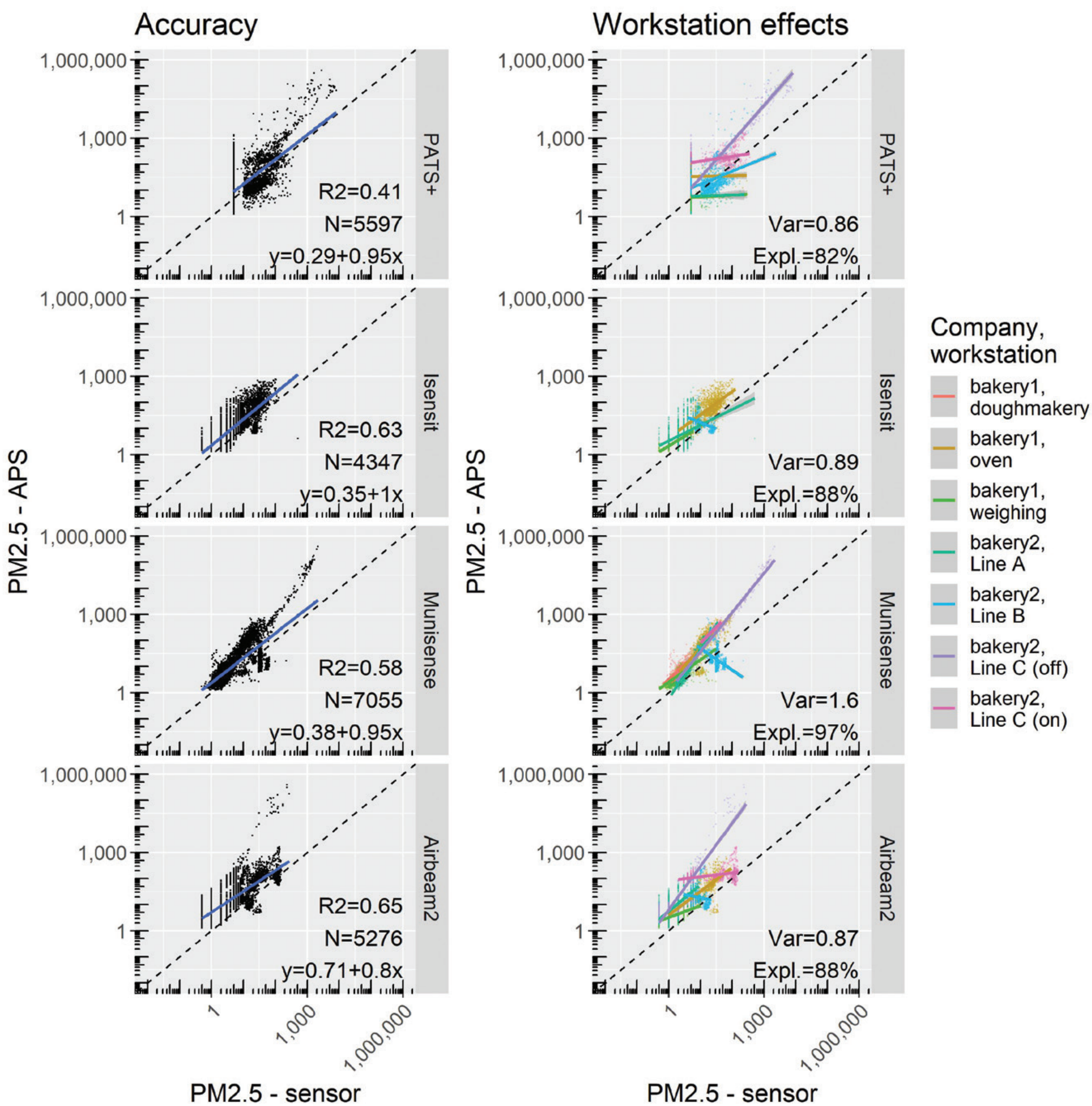

Figure 4. Stationary sensor performance for monitoring exposure over time at 1-min intervals. (a) Correlation between sensor and APS measurements and (b) effects of workstation. Var is the total amount of variance and Expl. is the percentage of variance explained by the workstation effect.

and the sensor reports measurement of 10 μg m^{-3} when it detects lower or no PM concentrations, in contrast to other sensors reporting 0 μg m^{-3}. When we removed the LOD measurements from the analysis, a correlation comparable to what is observed for the other sensors was found (R^2 of 0.61, Supplementary Fig. S5, available at *Annals of Work Exposures and Health* online). The Isensit, Munisense, and Airbeam reported 1, 0, and 15% of measurements below the LOD, respectively.

Measurements were averaged at 1-min intervals, which was arbitrarily decided to be frequent enough for time-resolved monitoring exposure. We investigated if averaging for longer periods would improve the accuracy. Averaging at 10-min intervals improved correlations slightly (up to 0.06) and further increasing the averaging period did not increase correlations (Supplementary Fig. S6, available at *Annals of Work Exposures and Health* online).

Similar to the first monitoring strategy, we investigated if the company (i.e. bakery 1 versus bakery 2) and workstation (smaller areas within the company where specific tasks are performed, leading to differences in aerosol and environmental conditions) had an effect on sensor performance. The workstation showed greater effects compared with the company (Fig. 4b, Supplementary Fig. S7, available at *Annals of Work Exposures and Health* online). Workplace effects were comparable for most sensors, except for the Munisense, for which the variance was twice those of the other sensors. Large effects (variations in performance) were observed between workstations, explaining over 80% of the total variance. This can be attributed to the fact that some sensors showed no or negative correlations at specific workstations. Interestingly, no specific workstation had a significant negative impact on the correlation of all sensors and the PM2.5 APS data. For instance, the workstation *Line B* showed negative correlations for the Isensit and Munisense, but not for the PATS+ and Airbeam2. Together, this shows that workstations within a company can have a large impact on the performance of the sensors.

Exposure monitoring strategy IV: ranking exposure periods within a shift

Performance for the ranking of 15-min periods within a shift (compared with the same periods measured by the APS) differed greatly between sensors, shown by the difference in median rank correlations as well as the large amount of variation for some sensors (Fig. 5). In this study, the Munisense showed relatively low variation and high median performance, with a median estimate of 0.78 and interquartile range (IQR) of 0.26. The PATS+ showed relatively low variation and low median performance (median 0.34, IQR 0.32) and

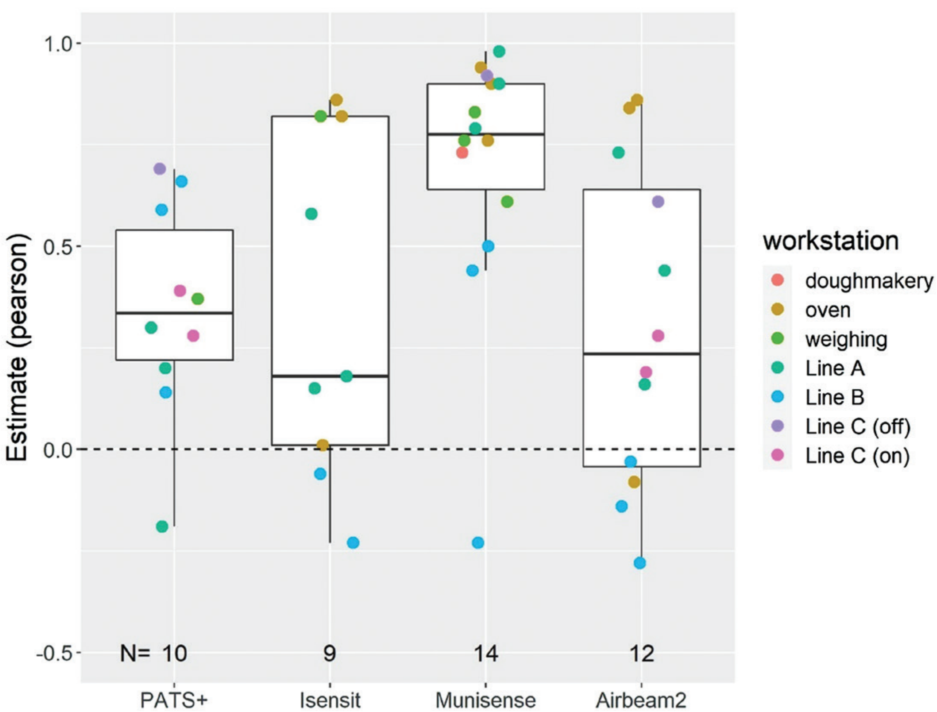

Figure 5. Within-shift rank correlations of sensors compared with APS. Each point represents the rank correlation of 15-min averages in an 8-h period, the color relates to the workstation where measurements were collected.

the Isensit and Airbeam2 showed both relatively high variation and low median performance (medians 0.18 and 0.24, IQRs 0.81 and 0.68). Extending the averaging periods to 30 or 60-minutes did not affect the interpretation of the results (Supplementary Fig. S8).

The workstation seems to influence the rank correlation. Specifically, measurements collected at the *Line B* workstation showed poor rank correlations, except for the PATS+. Although 8-h periods with relatively high average exposure levels showed high rank correlations for all sensors, no clear relationship between exposure levels and rank correlation could be observed.

Discussion

To explore how low-cost PM sensors can be applied for measuring exposure to hazardous substances, a field study was performed in the industrial bakery sector. Four types of sensor were used to collect data, as well as gravimetric and high-resolution reference devices. Four different exposure monitoring strategies were tested by comparing sensor measurements with reference measurements. Sensor performance improved and was more comparable between the tested sensors when ranking shift-average exposures compared with quantifying shift-average exposures. Ranking 15-min periods within a shift showed suitable for only one on the investigated sensors, while monitoring exposure at 1-min resolution seemed comparable between most sensors. Performance was comparable for most monitoring strategies when placed in stationary position and large differences between sensor types were found when worn by workers. The workplace and company were also found to be main sources of variance when high levels of variance were observed.

For the estimation of the average exposure during a shift, all four sensor types provided comparable results when placed in stationary position, with R^2 values between 0.39 and 0.63. For comparison, the APS, when compared with gravimetric respirable data, showed a R^2 value of 0.96. Large variations in performance were observed when worn by workers, with R^2 values of 0.60 versus −0.03. This indicates that sensor performance may differ depending on their placement (stationary versus personal). Similar results have been found for Sharp GP2Y1010AU0F PM sensors, which is a slightly older model of the sensing element used in the PATS+, where personal measurements showed lower correlations to gravimetric references and required different correction factors compared with stationary placed sensors in a heavy vehicle production factory (Zuidema *et al.*, 2019b). There is no information available in the literature regarding on why the performance of some sensors differ between personal and stationary placements. One explanation may be that the large amounts of movement when worn may change the direction or strength of the air sampling flow, as these sensors generally only use small, not so powerful fans for air intake.

In this study, the results showed that the sensors in stationary position provided better performance and better correlation between themselves compared with the sensors worn by workers. This is in line with multiple studies that report adequate sensor performance with relatively high R^2 values (ranging 0.7–0.9) when placed in stationary position in laboratory and in non-workplace indoor or outdoor settings (Kelly *et al.*, 2017; Pillarisetti *et al.*, 2017; Sayahi *et al.*, 2019; Tagle *et al.*, 2020).

We also observed that sensor measurements on a specific day may give a more accurate estimation of exposure than a gravimetric measurement from another day. This provides an argument for the benefit of a more continuous monitoring approach using low-cost sensors compared with fewer measurements with more validated, traditional methods, which is the current industry practice. It should however be noted that these are relatively few measurements in only one industry.

Ranking shift-average exposures showed less variation in performance between the sensors compared with the quantification of shift-average exposures, with Spearman correlations ranging 0.73–0.82. Additionally, the difference in performance between the low-cost sensors and the high-grade APS was smaller for the ranking shift-average monitoring strategy (Spearman correlations 0.73–0.82 versus 1.00), compared with the quantitative monitoring strategy (R^2 0.39–0.63 versus 0.96). This indicates that this semi-quantitative monitoring strategy may give a medium to small increase in accuracy compared with the fully quantitative monitoring strategy and gives less variation in performance between different types of sensor. This ranking monitoring strategy may therefore be a suitable alternative for identifying the highest exposure shifts, rather than a comparison based on quantitative differences. This could for instance be used to identify the shifts with highest average exposure of a given worker out of a prolonged measurement series or for identifying workers with higher average exposures, which fits well with the continuous and more widespread monitoring capabilities of low-cost sensors.

The performance for quantifying exposure with high temporal resolutions was similar for all tested sensors, with R^2 values ranging 0.58–0.65, with the exception of the PATS+. In this study, the relatively high LOD of the PATS+ had a moderate effect on the performance of this sensor, shown by the improved correlation after <LOD measurements were removed (R^2 from 0.41 to 0.61). The PATS+ has been developed for higher exposure concentrations, which is shown in previous

studies by the high accuracy of this sensors at ranges of 100–400 μg m^{-3}, albeit at medium resolutions of 1-h intervals (Pillarisetti *et al.*, 2017). This indicates that the operation range of sensors may be important to consider, also at lower concentrations.

The semi-quantitative monitoring strategy of ranking smaller periods within a shift only proved to be suitable for only one of the tested sensor types (median Pearson correlation of 0.78 and IQR of 0.26), shown by the low median rank correlations (ranging 0.18–0.34) and high variation (IQR ranging 0.32–0.81) for the other three sensors types. This difference in performance could be due to relatively higher performance for the Munisense at lower concentrations (shown as a relatively higher correlation at lower concentrations in Fig. 3). These results show that this method may be less suitable for identifying moments of relatively high exposure during a shift, warranting investigations to alternative methods in future research. Alternative semi-quantitative methods could, for instance, be based on detecting exposure concentrations surpassing a (relative) threshold value for a set duration (de Kluizenaar *et al.*, 2017), or by detecting relative changes in exposure concentrations.

For all exposure monitoring strategies that were investigated, sensor performance was found to differ between the companies and workstations where measurements were collected. These effects may be explained by the sensitivity of the PM monitors to environmental interferants such as particulate density, refractive index, particle size distribution, and exposure transiency (Ruiter *et al.*, 2020; Huang *et al.*, 2021; Sousan *et al.*, 2021). Changes in these interferants can differ between companies or workstations and may be more prominent during personal measurements due to movement of workers and the task specificity of flour dust exposure (Meijster *et al.*, 2008), which also could explain the large variation in performance for personal applications.

Altogether, this study presents a first exploration of different exposure monitoring strategies of low-cost PM sensors. Occupational exposure to flour dust remains a relevant problem in the Netherlands, shown by the introduction of a legal limit value in 2020 (1.2 mg m^{-3} inhalable dust), meaning additional or new control strategies are necessary. Sensors provide new possibilities for monitoring exposure, but guidance for their practical application is lacking. We provided a first overview of possible methods for the use of sensors to potentially minimize exposure in the workplace and reduce occupational diseases.

We investigated how several external factors and methodological choices may affect the performance of sensors for different monitoring strategies. Identification of these parameters can be a starting point for improving the use of sensors in the workplace. For instance, this information could be collected in guidance documents to aid users in appropriate application of sensors in the workplace or may give focus to the development of new data analysis methods. It should be noted that this study focused on comparing different methodologies, rather than provide a complete performance assessment of the low-cost PM sensors.

The current study has some limitations. One is that the company or workstation was used as a proxy for differences in environmental situations. While effects for the company and workstation were observed (40–97% of variance explained in high variance situations), we did not specifically investigate which environmental interferants caused the effects, or how these differ between the companies or workstations. Identifying which specific parameters affect sensor performance in the workplace and how to correct for these factors is an important aspect for future research to increase the performance of low-cost PM sensors. Another limitation is that this study compared PM2.5 fractions from the sensors with respirable dust fractions measured by the gravimetric samplers. This fraction was used since all sensors reported PM2.5, while none of the sensors reported respirable dust or even PM4. Furthermore, it should be noted that flour dust comprises of relatively large particles. Previous studies report that 20% of the total dust is in the respirable fraction. This might cause interference with the sensor measurements, since no size selection mechanisms are present at the inlet.

Additionally, the study describes the overall use of sensors for assessing occupational exposures, while measurements were collected only in the industrial bakery sector. More field research in additional industries is needed to confirm the findings in these studies. These additional studies could be improved by the inclusion of a personally worn high-resolution reference device to further investigate the difference in stationary or personally worn sensors.

Conclusions

Exploration of four different exposure monitoring strategies of four types of low-cost PM sensors in the industrial bakery sector provided insights in how sensors can be used in the workplace. Semi-quantitative monitoring strategies based on ranking exposures rather than quantifying them increased overall sensor performance for monitoring strategies based on the average exposures over a shift, but not for monitoring exposure over time. Performance of low-cost sensors was found to be more robust in stationary position compared with personal ones. Additionally, the measurement location between or within a company can have a large effect on the performance of the sensor.

Together, these findings provide a starting point for further research regarding the application of low-cost sensors in the workplace, such as the development of guidance documents and data analysis or processing methods.

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Disclaimer

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Conflict of interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Data availability

The data underlying this article will be shared on reasonable request to the corresponding author.

Supplementary data

Supplementary data are available at *Annals of Work Exposures and Health* online.

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